Quantifing Errors Associated with Satellite-Derived Data Sets

A feeble attempt to initiate a discussion with NASA Science Teams

Peter Cornillon

University of Rhode Island

New Orleans
Earth Science Data System Working Groups'

joint meeting

20 October 2009

Outline

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1. The Poll

2. Spatial Fidelity

Introduction

- 17 August Product Quality Metrics Telecon I suggested
  - Including the quality of spatial information as a fundamental data set metric
  - Gathering information from NASA Science teams about their plans/approaches to quality metrics
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  - Merging 10 to 11 satellites
  - 31 years
- Measuring reflectivity back to space.
- No ground-based data for validation.
- Two approaches to validation and error estimates.
  - Compare ground irradiance estimated from reflected energy reaching space with ground-based irradiance measurements.
  - Consider the precision of the data rather than their accuracy.
    - Based on initial laboratory calibration of the satellite instrument.
    - From ice reflectivity measurements in flight.
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  - We identify a minimum list of criteria for data quality on which we all agree.
    - If too long of a list, people will not provide the metrics
- Focus on one example first and then see how it can be generalized.
- Values without error bars are almost meaningless.
  - It is doubtful that a product without error bars can be classified as "high quality"
- Error bars in atmospheric composition tend to come as:
  - Precisions on individual profiles
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    - Although SST is the most completely sampled parameter of the Earth system, there are regions that are undersampled
        - Poleward of 60°
        - Upwelling zones (thinking IR here)
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    - It is not a direct measure of uncertainty associated with the SST of a given pixel
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- A pre-SSTST workshop was held in Rhode Island in November 2009
  - Workshop objective was to characterize the SST error budget
  - An SST error budget white paper was produced following the workshop: http://www.ssterrorbudget.org/ISSTST/White_Paper.html

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SST Requirements

- A set of SST requirements was developed at the workshop:
  - Requirements previously identified.
    - These tended to focus on model and operational requirements.
  - Those identified by workshop participants
    - Represented a significant community not considered in previous work
    - These requirements tended to be more stringent than previous ones.

Application	**Source**	**Spatial resolution** (km)	**Temporal resolution** (hrs)	**Geolocation accuracy** (km)	**Absolute accuracy** (K)	**Relative accuracy**
CDR	Ohring et al., 2005				0.1	0.04°K/decade
CDR	Appendix II					0.05°K/decade
NWP	Eyre et al., 2009	5	3		0.3	
Global Operations	NPOESS IORD-II	0.25	3	0.1	0.1	0.05°K
Coastal/Lake Operations	NPOESS IORD-II	0.1	6	0.1	0.1	
Fronts	Appendix II	0.1	0.25	0.1	1	0.1°K
Climate Models	Appendix II	25	24	5	0.2	0.05°K/decade
Lakes	Appendix II	1	3	1	0.3	0.2°K
Air-sea fluxes	Appendix II	10	24	2	0.1	
Mesoscale	Appendix II	1	168		0.1	0.1°K
Submesoscale	Appendix II	0.1	24		0.1	0.1°K
Strictest		0.1	0.25	0.1	0.1	0.05°K 0.04°K/decade

SST Requirements

- A set of SST requirements was developed at the workshop:
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Application	Source	Spatial resolution (km)	Temporal resolution (hrs)	Geolocation accuracy (km)	Absolute accuracy (K)	Relative accuracy
CDR	Ohring et al., 2005				0.1	0.04°K/decade
CDR	Appendix II					0.05°K/decade
NWP	Eyre et al., 2009	5	3		0.3	
Global Operations	NPOESS IORD-II	0.25	3	0.1	0.1	0.05°K
Coastal/Lake Operations	NPOESS IORD-II	0.1	6	0.1	0.1	
Fronts	Appendix II	0.1	0.25	0.1	1	0.1°K
Climate Models	Appendix II	25	24	5	0.2	0.05°K/decade
Lakes	Appendix II	1	3	1	0.3	0.2°K
Air-sea fluxes	Appendix II	10	24	2	0.1	
Mesoscale	Appendix II	1	168		0.1	0.1°K
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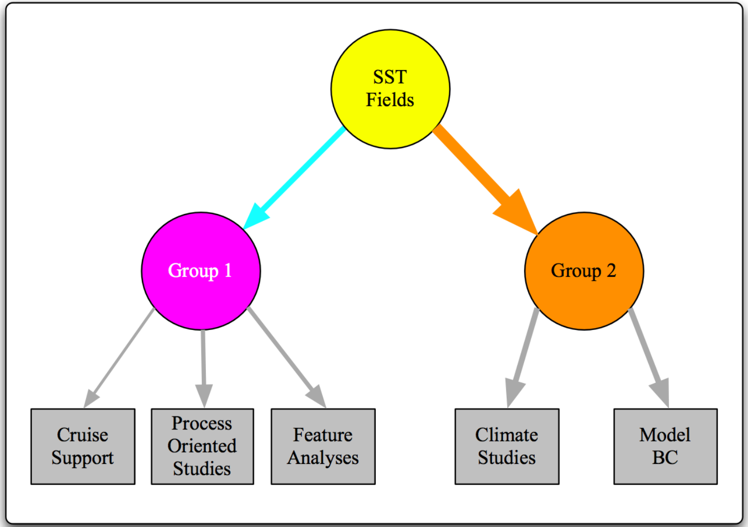
Feature versus Climate Studies



Data Set Quality Metrics

- Satellite-derived Earth science data sets are rich both
  - Temporally, and
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- However, we rarely evaluate the quality of spatial information in our data products.

Although the previous and following comments may apply to other Earth science disciplines Those presented here are based on observations associated with ocean products.

- Primary focus of the quality of most satellite-derived products is on ‘point’ accuracy.
  - The mean and RMS difference of $SST_{satellite} - SST_{in\_situ}$
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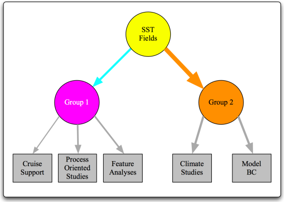

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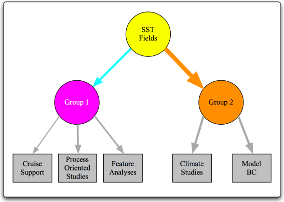

Data Set Quality Metrics

Peter Cornillon

The Poll

Spatial Fidelity

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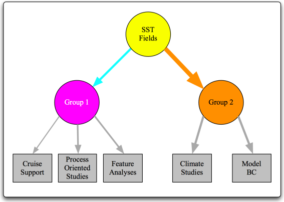

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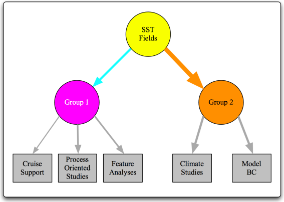

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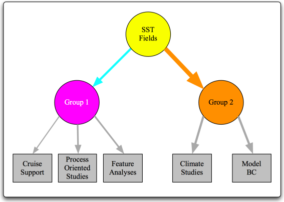
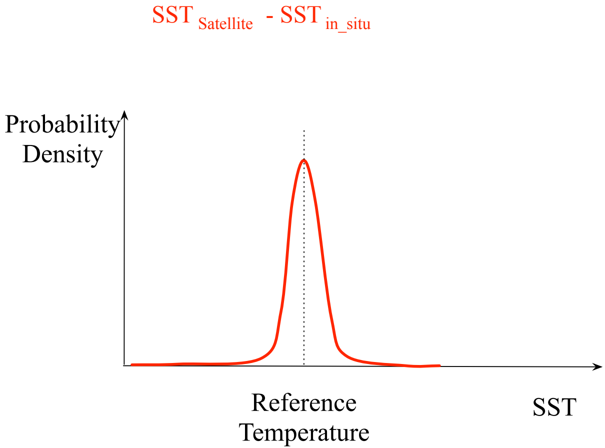


Conclusion from SST Error Budget Whitepaper

New requirements point to the need for a measure of the spatial fidelity of SST products.

Accurate and Precise



Small scatter, no bias

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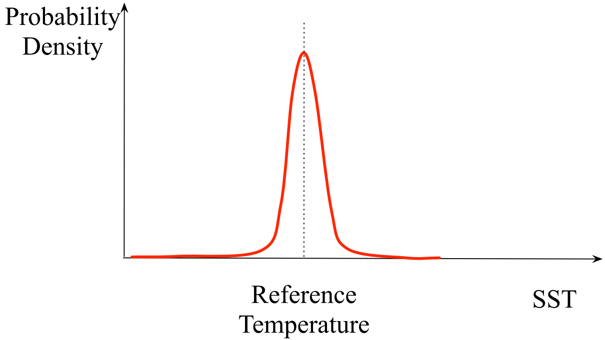

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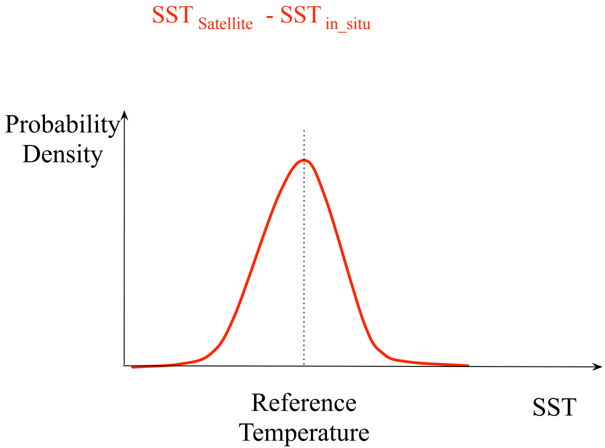

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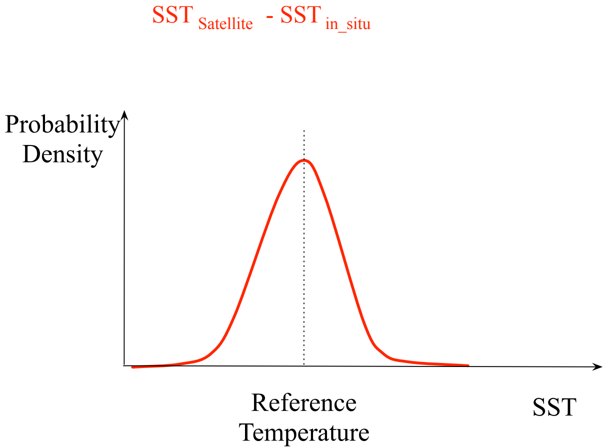

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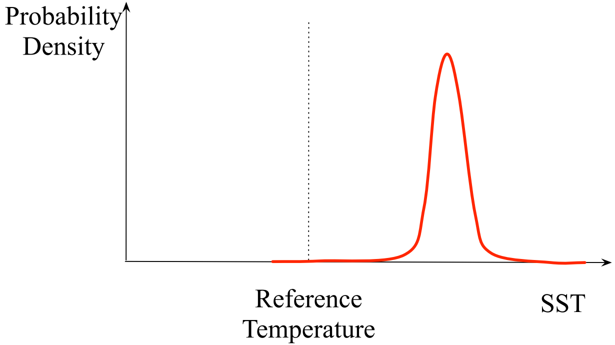

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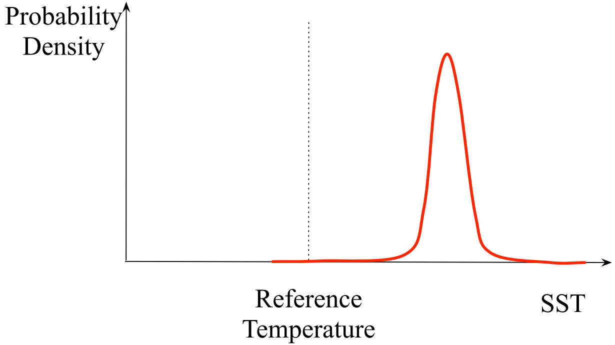

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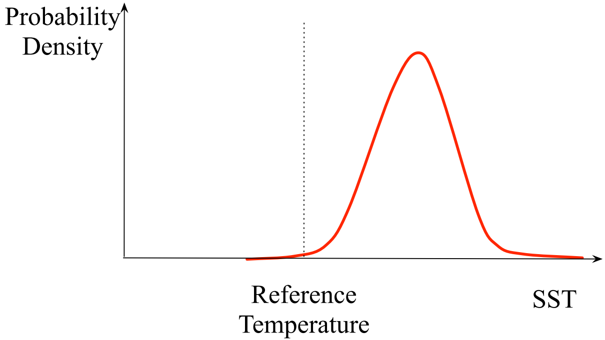

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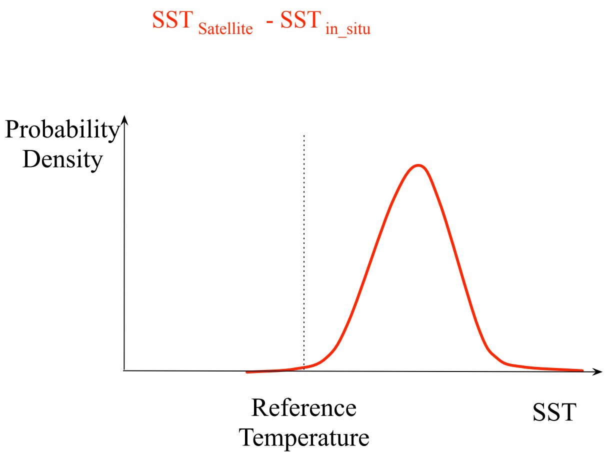

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Conclusion from SST Error Budget Whitepaper

That was cool.

Now let's look at these distributions in the context of the point-to-point (spatial) difference in an SST field.

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Accurate and Precise; Small Point-to-Point

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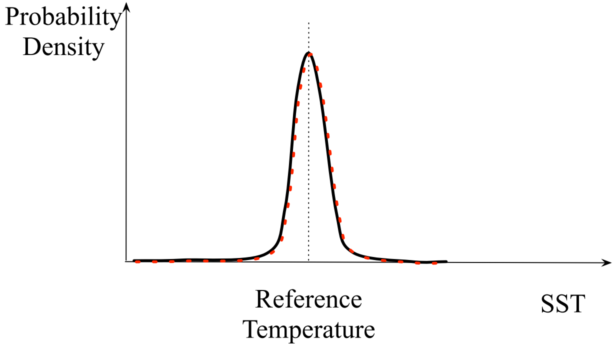

Small scatter, no bias when compared with in situ observations and small point-to-point variabiility

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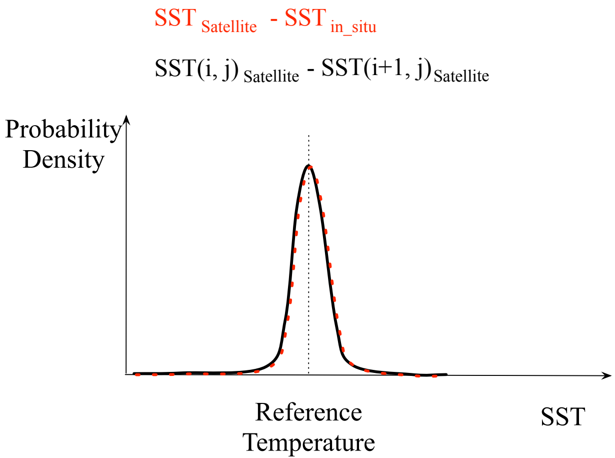

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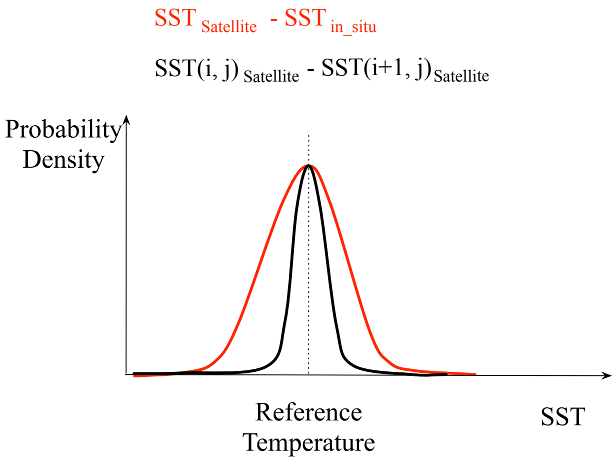

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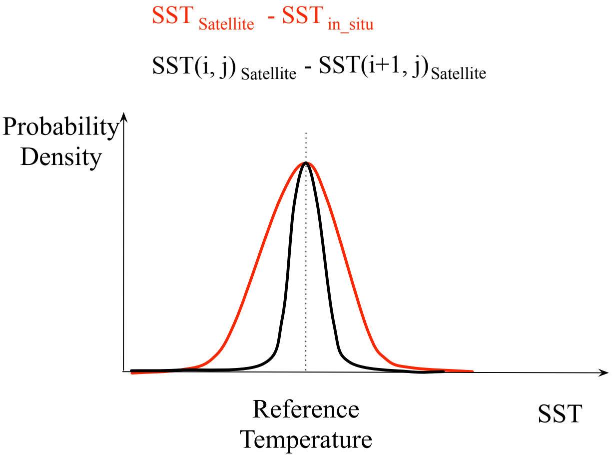

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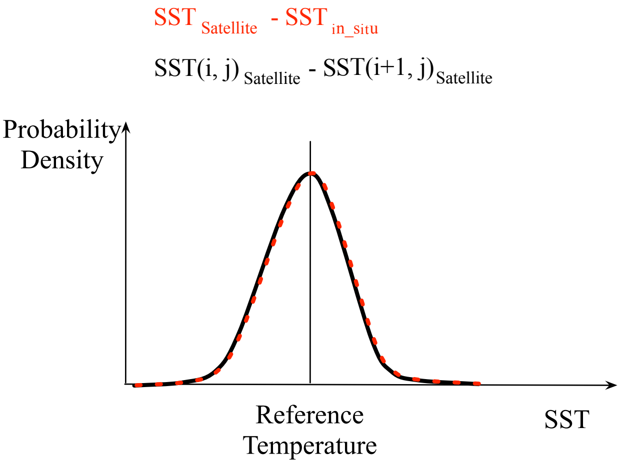

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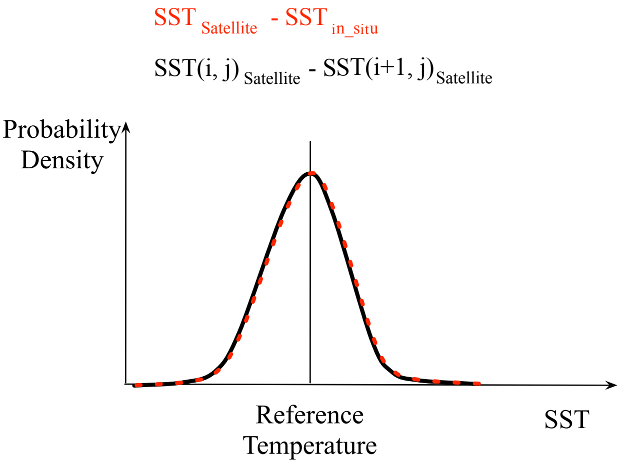

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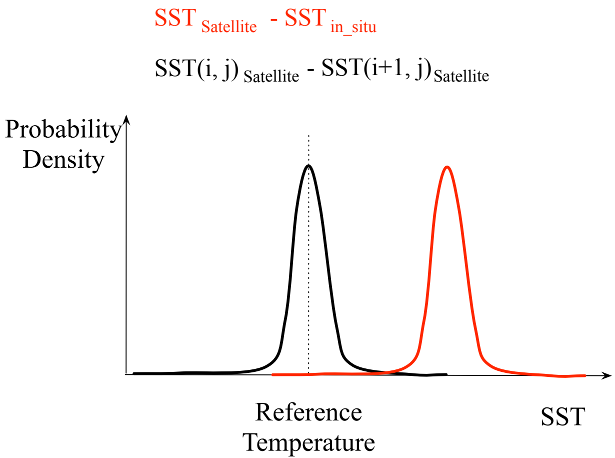

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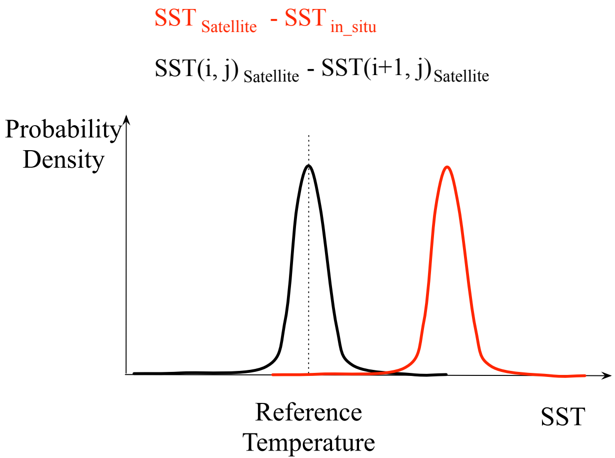

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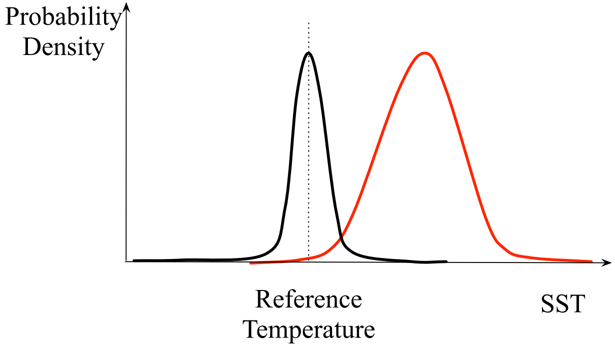

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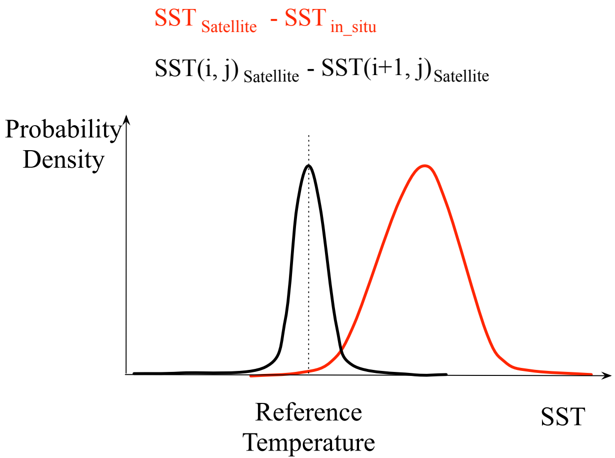

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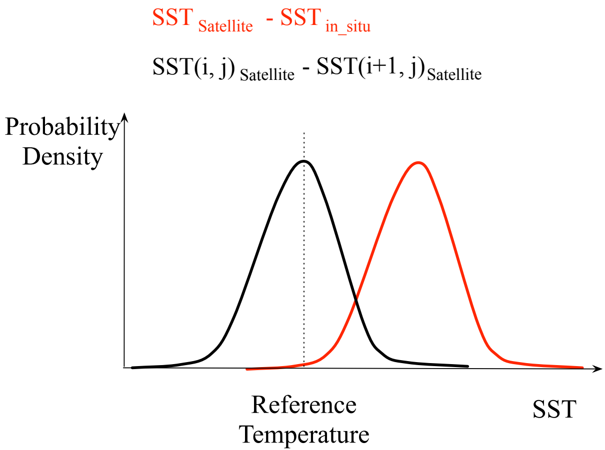

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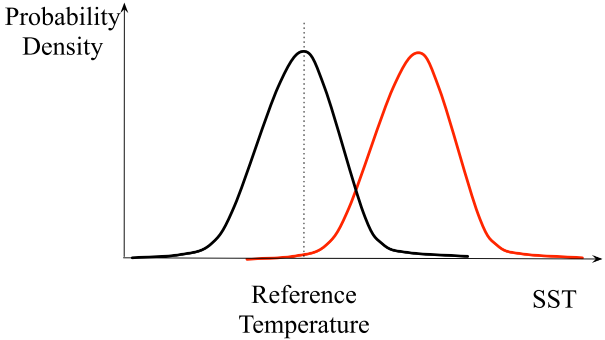

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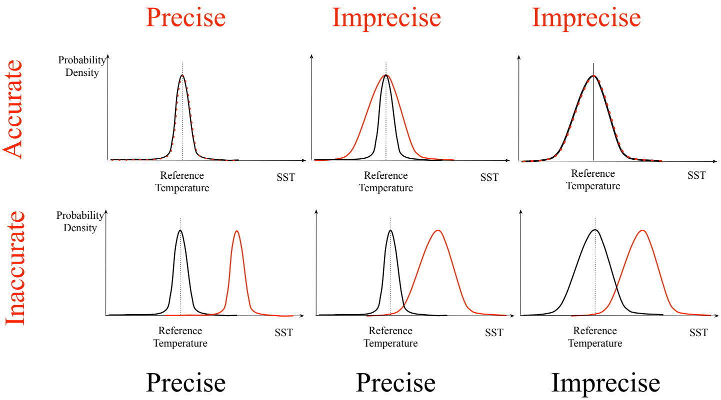
All Together Now

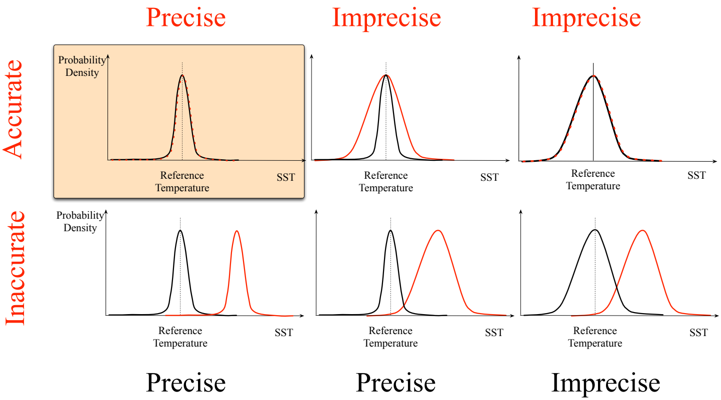


All Together - Climate Studies

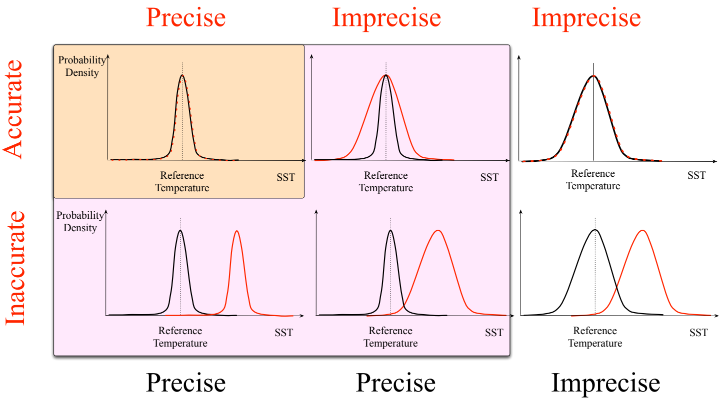
Peter Cornillon

The Poll

Spatial Fidelity



All Together - Feature Studies



Examples: Case 1

Let's look at a couple of simple statistics for two different cases.

- Comparison 1: For the western North Atlantic
    - The data sets
        - MODIS - 4km global for 2008
        - AVHRR Pathfinder v5 - 4km global for 2008
    - The statistic
        - The standard deviation for each 3x3 pixel tile in each image.

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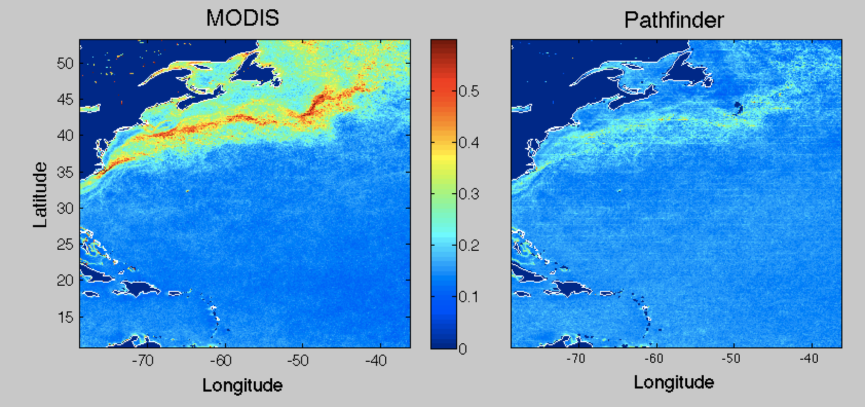
Standard Deviation on 3x3 Tiles



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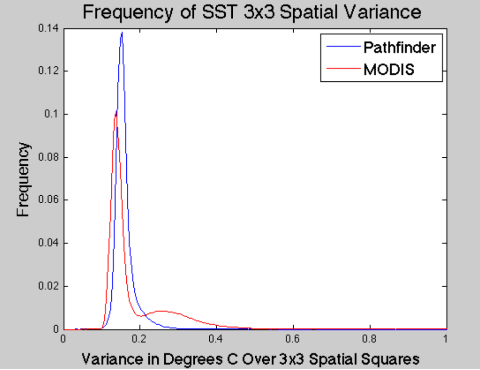

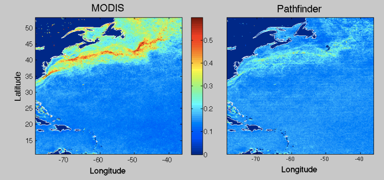

Examples: Case 2

And

- Comparison 2: For the world ocean
  - The data sets
    - Level 2 AMSR-E from RSS oversampled to 10km resolution (middle 160 pixels on each scan line).
    - Level 3 AMSR-E from RSS obtained from L2 and reprojected to a 25km resolution map.
  - The statistic
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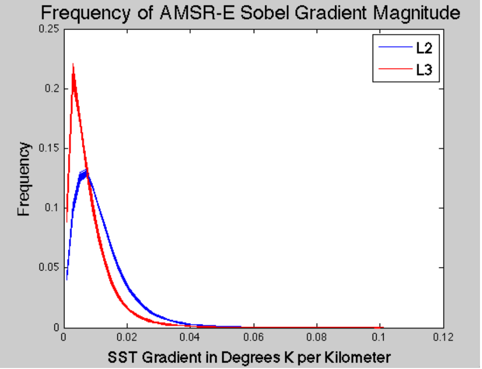
Sobel Gradient Magnitude for L2 versus L3 AMSR-E



Seems reasonable:

- The L2 product is 10km resolution so allows for larger gradients than 25km L3
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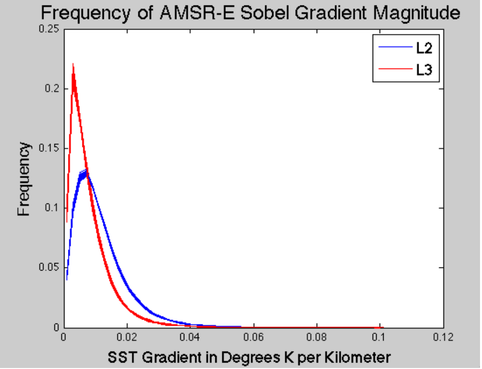

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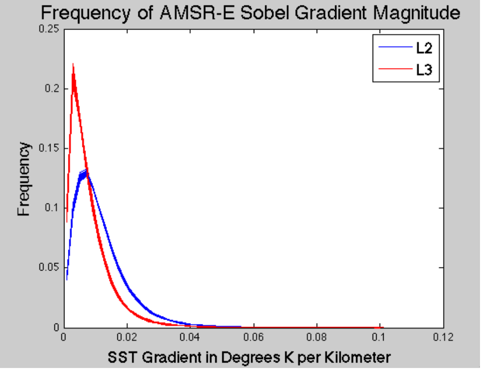

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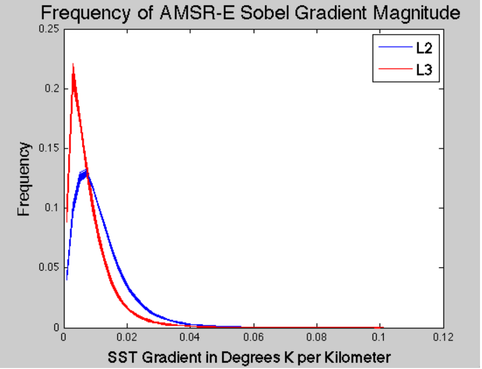

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- Two similar sensors with similar processing (MODIS/AVHRR)
- Yield quite different results for a statistic related to the spatial variability of the fields.
- Two data sets from the same sensor but in different projections (L2/L3)
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It seems a shame to spend BILLIONS of $s on collecting data and then to ignore some of their richness.

All Done

The End